Market Prediction as a task for AGI Agents

James Oswald

Rensselaer AI and Reasoning Lab

The 15th International Conference on Artificial General Intelligence
8/20/2022

Overview

This work investigates the utility of market prediction as a task for AGI agents due to its dual logical and statistical nature.

We propose a modified version of the market prediction task that can be played by all types of different agents beyond just statistical agents.

We propose a dataset inline with past benchmarks for our task, and benchmark multiple methods, including NARS on the task.

Precursors

Traditional Market Prediction Task

Market prediction can be phrased as a time series prediction task.

We learn a model f that at time t, can predict the asset price, p, at time, t+i, when given past prices and additional observations, x.

$$p_{t+i} = f(i, p_{t-k:t}, \mathbf{x})$$

Machine Learning for Stock Market Prediction

- *Technical Data* is inherently quantitative, and is essentially just the price histories of assets. As well as other computed indicators

- Fundamental Data is much more *qualitative* and includes:
    - Earnings reports
    - News about the asset
    - Social media mood
    - Posts about the asset on blocks and forms.

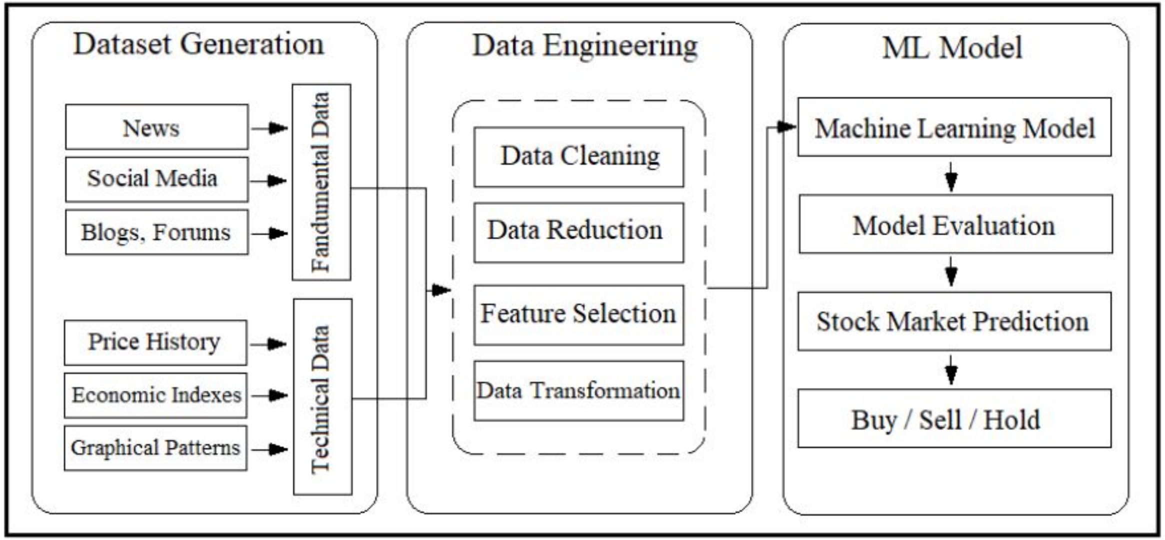
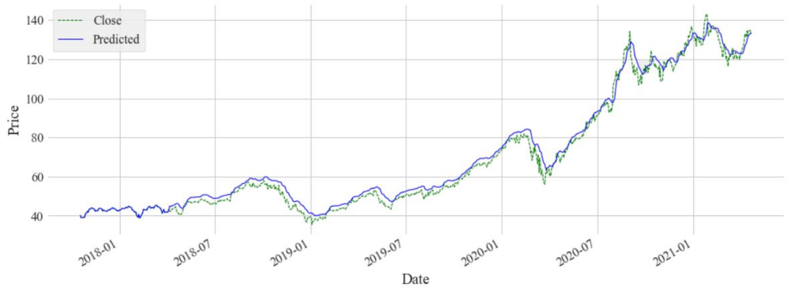


Figure from Mokhtari et al. (2021)

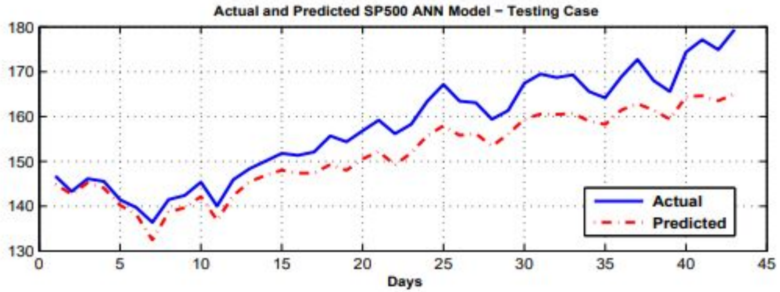
Statistical Method Results

All shown results predict closing prices of next day with data from previous days



(b) Prediction of the LSTM model.

Using an LSTM for predicting APPL Price with technical indicators. Mokhtari et al. (2021)



Predicting S & P 500 Price with technical indicators with a simple ANN. Sheta et al. (2015)

Metrics	LR	GNB	BNB	DT	RF	KNN	SVM	XGB	ANN
Precision	0.729	0.636	0.644	0.620	0.727	0.684	0.757	0.710	0.684
Recall	0.727	0.634	0.644	0.620	0.727	0.684	0.755	0.709	0.684
F1-score	0.726	0.632	0.644	0.620	0.727	0.684	0.755	0.709	0.684
Accuracy	0.727	0.634	0.644	0.620	0.727	0.684	**0.755**	0.709	0.684
AUC	0.73	0.63	0.64	0.62	0.73	0.68	0.76	0.71	0.68

Comparison of Statistical and ML Market forecasting methods with quantitative fundamental indicators. Mokhtari et al. (2021)

Shortcomings of Statistical & Connectionist Approaches

- Mokhtari et al. (2021) tested many ML methods and found that while the price of a stock at the end of the day can be predicted with ~65% accuracy when given both technical factors but find it is completely unable to generalize this even one day out.
- Qualitative fundamental data is difficult for machine learning methods to interpret and take advantage of without logic based reasoning capabilities.
- Explainability is a huge issue with all machine learning techniques, we would like human level insight into why a model believes an asset price will go up or down.

A Modified Market Prediction Task for AGI

Task

Given a set of n, (27 in our case) qualitative technical factors {$\boldsymbol{f}_1$, …, $\boldsymbol{f}_{27}$} and the price of the S & P 500, ***p***, with a daily magnitude change ***m*** and direction ***d*** components over the course of 10 years. Create an agent **A** which takes these factors of the previous day (at time ***t***) and maximizes its ability to predict the direction the S & P 500 moves the following day $\boldsymbol{p}^{d}_{t+1}$

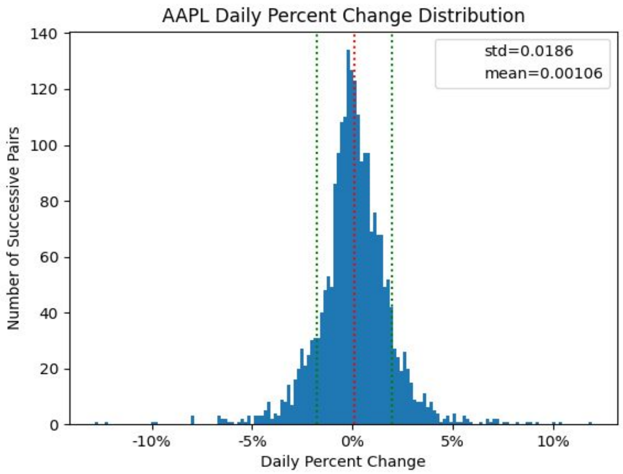
$$F_t = \{f^m_{1t}, f^d_{1t}, \cdots, f^m_{27t}, f^d_{27t}\}$$

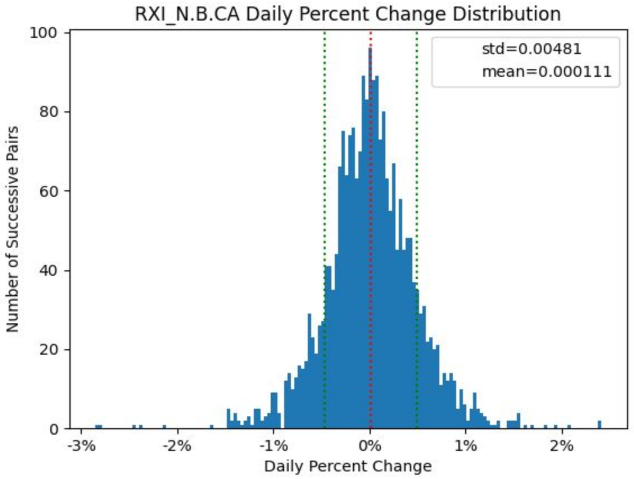
$$A(p^d_t, p^m_t, F_t) = p^d_{t+1}$$

Qualitative Conversion

Problem at hand

- Different assets have wildly different price distributions.
- A 1% change in in one asset may be huge for one asset while just average for another.
- When representing the magnitude of daily change we want to ensure this distribution is reflected fairly.





A Solution, Z-Score bucketing

- Use past distribution of asset percent and current daily change to to compute "Significance" of the price movement with respect to that asset.
- Use Z-Score (Number of standard distributions away from the average) as a measure of significance.
- Bucket Z-score into a group with a label corresponding to magnitude.

Example Conversion

Apple Daily Stock Price:

Date	Price
2012-01-30	$14.57
2012-01-31	$15.08

Percent Daily Change:
($15.08-$14.57)/$14.57 = 3.5%

Standard Deviation for Apple = 1.8%
Z-Score = (3.5%-0.1%)/1.8% = 1.89

→ Direction: +1   Magnitude: 2

If Z-Score is negative then the direction is set to -1, else, +1.

Magnitude is determined by bucketing Z-scores:
Z-Score between [0,1) => 1
Z-Score between [1,2) => 2
Z-Score > 2 => 3

Our Data

Data Sources

- Daily values of 29 technical market factors over past 10 years across 5 groups:
    - 2 Commodities
    - 4 Currency Exchange Rates
    - 6 Global Stock Market Indexes
    - 7 Bond Yield Rates
    - 10 High Profile Stocks
- Selected factor groups were influenced by previous ML work which uses many of the same groups.

Commodities

The 2 commodities selected are:

- Daily Gold Prices sourced from the NASDAQ
    - Supposedly an indicator of public faith in market, however, this is contested (NBER)
- Daily WTI Crude Oil Prices sourced from the U.S. Energy Information Administration
    - Oil prices correlate with stock prices of companies involved in transportation and energy (EIA)

Currency Exchange Rates

Selected Daily Currency Exchange Rates all sourced from the Federal Reserve H.10

- GBP (British Pounds) to USD
- JPY (Japanese Yen) to USD
- CNY (Chinese Renminbi) to USD
- CAD (Canadian Dollars) to USD

There is a substantial body of literature on currency exchange rates impacting stock market prices (Cakan & Ejara)

Global Market Indexes

Daily closing prices of the following global market indexes

- S&P 500, sourced from the NASDAQ
  - Considered the best representation of the state of the US stock market
- Hang Seng Index, sourced from Yahoo Finance
  - Benchmark of the Hong Kong stock market
- CAC 40, sourced from Yahoo Finance
  - Benchmark of the French stock market
- FTSE 100, sourced from WSJ Markets
  - Benchmark of the British stock market
- DAX, sourced from Yahoo Finance
  - Benchmark of the German stock market

Bond Yield Rates

Moody's Daily Corporate Bond Yields sourced from FRED

- AAA ranked corporate bonds with maturities over 20 years
- BAA ranked corporate bonds with maturities over 20 years

Daily Treasury Bond Market Yields sourced from The Federal Reserve H.15

- 3-month maturity
- 6-month maturity
- 1 year maturity
- 5 year maturity
- 10 year maturity

Bond prices are well known to be inversely correlated with the stock prices.

Stocks

Daily closing prices of prominent stocks sourced from Yahoo Finance

Current top five S&P 500 stocks as of 3/27/22

- Apple
- Microsoft
- Amazon
- Google Class A
- Google Class C

Others:

- Exxon Mobil
- General Electric
- Proctor and Gamble
- Johnson and Johnson
- Berkshire Hathaway Class A

Data Preparation

Input data

Data comes in as CSV files in different formats

```
Date,Open,High,Low,Close,Adj Close,Volume
2012-01-30,287.945709,288.917053,285.629395,287.766388,287.766388,4678471
2012-01-31,290.411469,290.909607,286.501129,288.971863,288.971863,4300860
2012-02-01,291.377838,291.656799,288.488678,289.330505,289.330505,4658797
2012-02-02,291.342987,292.110107,289.953186,291.462524,291.462524,4847502
2012-02-03,294.227173,297.420197,292.927032,297.051575,297.051575,6360753
2012-02-06,296.394043,304.274506,295.895905,303.407745,303.407745,7386784
2012-02-07,302.441376,303.557190,300.752716,302.252075,302.252075,4199883
2012-02-08,303.183594,304.533539,301.240875,303.786346,303.786346,3686567
2012-02-09,304.867279,306.102661,303.362915,304.588318,304.588318,4546377
2012-02-10,302.805023,302.929535,300.872253,301.823700,301.823700,4667831
2012-02-13,304.110107,305.773895,303.871002,304.956940,304.956940,3646216
2012-02-14,304.628174,304.857330,301.250824,303.741516,303.741516,3620921
2012-02-15,305.320587,305.320587,300.154938,301.649353,301.649353,4869986
2012-02-16,300.284454,303.268280,297.748962,302.127563,302.127563,5080773
```

10 years of GOOGL market data from Yahoo Finance

```
Date,Close
2012-01-30,3.77
2012-01-31,3.72
2012-02-01,3.80
2012-02-02,3.79
2012-02-03,3.93
2012-02-06,3.87
2012-02-07,3.92
```

FRED Corporate Bond Yield Data

```
"Series Description","UNITED KINGDOM -- SPOT EXCH
"Unit:","Currency:_Per_GBP","Currency:_Per_USD","
"Multiplier:","1","1","1","1"
"Currency:","USD","CAD","CNY","JPY"
"Unique Identifier: ","H10/H10/RXI$US_N.B.UK","H1
"Time Period","RXI$US_N.B.UK","RXI_N.B.CA","RXI_N
2012-01-02,ND,ND,ND,ND
2012-01-03,1.5655,1.0089,6.2940,76.6700
2012-01-04,1.5638,1.0134,6.2941,76.6800
2012-01-05,1.5480,1.0197,6.3013,77.1800
2012-01-06,1.5431,1.0231,6.3088,77.0600
2012-01-09,1.5436,1.0272,6.3143,76.8800
2012-01-10,1.5489,1.0161,6.3141,76.8400
2012-01-11,1.5325,1.0192,6.3149,76.9000
2012-01-12,1.5325,1.0197,6.3177,76.7600
2012-01-13,1.5301,1.0246,6.3065,76.9000
2012-01-16,ND,ND,ND,ND
2012-01-17,1.5356,1.0130,6.3136,76.8000
```

Federal Reserve H.10 Currency Exchange Rates

```
Date,Close,Volume,Open,High,Low
03/28/2022,4575.52,--,4541.09,4575.65,4517.69
03/25/2022,4543.06,--,4522.91,4546.03,4501.07
03/24/2022,4520.16,--,4469.98,4520.58,4465.17
03/23/2022,4456.24,--,4493.1,4501.07,4455.81
03/22/2022,4511.61,--,4469.1,4522,4469.1
```

NASDAQ S&P 500 closing records

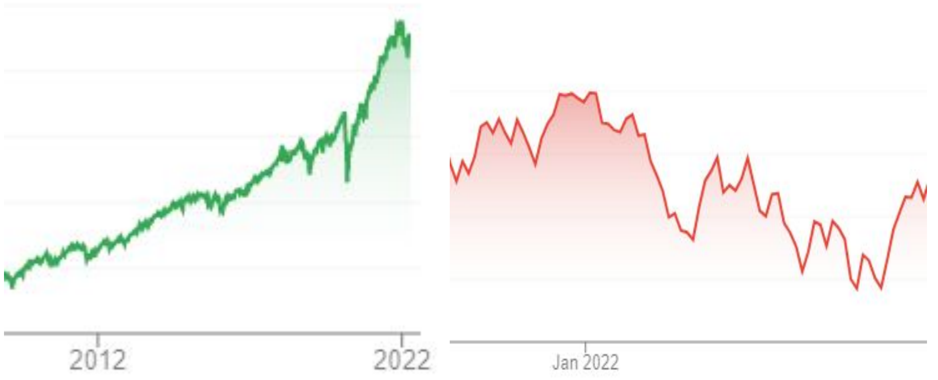
Dataset Processing Pipeline

Converting all input data files into single unified dataset for learning

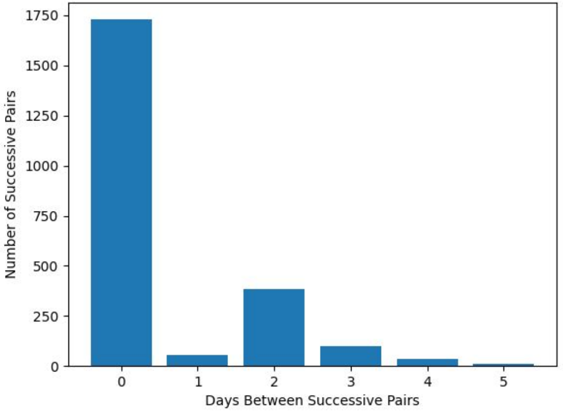
1. Unique processing for each file source type into one big buffer with all data arranged by date
2. Clean the data by removing dates with no info (weekends and market holidays as well as other errors)
3. Transform the data from quantitative into qualitative via Z-score bucketing
4. Write unified dataset to a unique file

A Few Issues

- Benchmark train and test set have different distributions.



- Weekends and market holidays lead to gaps in the data.



Agents & Results

Benchmark Statistical & Connectionist Agents

- Multi Linear Regression Agent
  - Performs linear regression to find coefficients for factors in a linear function that predicts the direction.
- Multi Logistic Regression Agent
  - Same idea as multi-linear regression but with logistic regression over the high dimensional space.
- SVM Agent
  - Uses a support vector machine to predict direction movement from factors
- ANN Agent
  - Multilayer perceptron 1 hidden layer with 100 neurons
  - Relu activation

Baseline Agent Results

Agent	Train Accuracy	Test Accuracy
Multi Linear Regression	65.03%	**64.81%**
Multi Logistic Regression	65.17%	63.58%
SVM	55.09%	51.23%
ANN	65.45%	64.19%

NARS Agents

- Sequence agent (Produces an action (direction guess) from a sequence of features)
- Inheritance Agent (Feature products *are* directions)
- Logical Agent (Feature products *logically entail* directions)

```
//NARS Inheritance Agent
//Input
<(f1 x f2 x ... x f27) --> S&P500_Up>. :|:
//Test Query
<(f1 x f2 x ... x f27) --> ?S&P500_Direction>?
```

```
//NARS Logical Agent
//Input
<(f1 x f2 x ... x f27) ==> S&P500_Up>. :|:
//Test Query
<(f1 x f2 x ... x f27) ==> ?S&P500_Direction>?
```

```
//NARS Sequence Agent
//Inputs            //Queries
<f1>.               <f1>.
<f2>.               <f2>.
...                 ...
<f27>.              <f27>.
<^S&P500_Up>.       //goal <predict>.
<predict>.          //Recive output actions
```

NARS Agent Results

Agent	Train Accuracy	Test Accuracy
NARS Sequence	Negligible	Negligible
NARS Inheritance	56.17%	54.39%
NARS Logical	62.76%	60.49%

Not better than most baselines… So why use it?

Summary

Table 2: Results of all of our agents

Method	Train	Test
Random Baseline	55.23%	49.3%
MLR	65.03%	64.81%
MLogR	65.17%	63.58%
SVC	55.09%	51.23%
ANN	65.45%	64.19%
NARS	62.76%	60.49%

Explainability

We can query NARS about its internal beliefs, while we can ask:
“What direction will the S&P 500 move in based on these factors f”
<(f1 x f2 x ... x f27) ==> ?S&P500_Direction>?

We can just as easily ask:
“What factors most cause the S&P 500 to go up?”
<?Factors ==> S&P500_Up>?
“What factors most cause the S&P 500 to go down?”
<?Factors ==> S&P500_Down>?

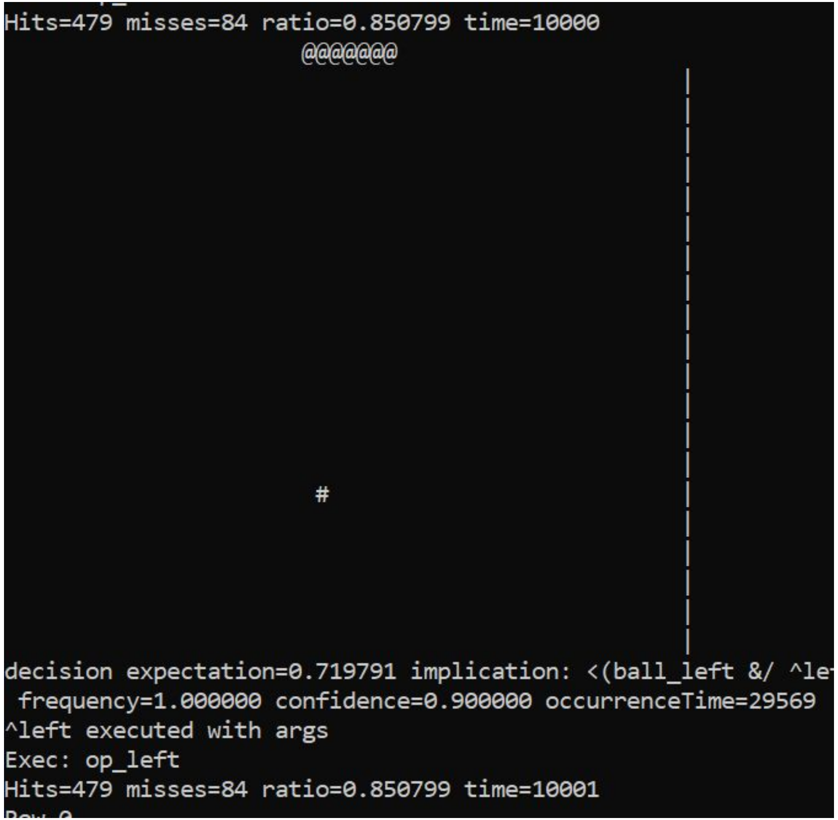
```
Answer: <(FTSE_Direction_1 * (SPX_Direction_1 * (GOOG_Direction_1 * (HSI_Direction_1 * FCHI_Direction_1)))) ==> SPXp1_0>. c
reationTime=2151 Truth: frequency=1.000000, confidence=0.990000
Answer: <(FTSE_Direction_0 * (SPX_Direction_0 * (GOOG_Direction_0 * (HSI_Direction_0 * FCHI_Direction_0)))) ==> SPXp1_1>. c
reationTime=2141 Truth: frequency=1.000000, confidence=0.990000
```

Generality: Procrastinating NARS Agent

The agent first trains on and masters how to play pong, hits 85% of the balls thrown at it.

It then learns how to predict the S & P 500 price with 56% accuracy.

Then goes back to learning to play pong getting up to 88% accuracy.



End